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Artificial Intelligence Based Framework For Academic Performance Visualisation

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Abstract— Schools are embracing the use of data-driven information to track student achievement and performance. Conventional ways of tracking performances are not effective in the intricate nature of the relationships among diverse academic contributions. This research works on the necessity of an efficient, but simple, artificial intelligence based framework to examine and visualize the factors mentioned and to take proactive measures that will help find out students who might not need more than a top-quality academic assistance. The main purpose of the research is to come up with a machine learning model that is easy to interpret, has the predictive strength of the end-of-year academic scores and classifies students into groups of "pass" and "fail." Also, the research will visualise the relationship between particular inputs (ex: hours of study, attendance) and performance in general and characterize a feature importance analysis to determine which factors have the most profound impact on student achievement. The research works with the artificial data including major academic variables: study hours, attendance, assignment grades, internal grades, and past GPA. The methodology will use two different machine learning models: Linear Regression to predict continuous performance scores and Decision Tree Classification to perform binary categorisation (Pass/Fail). Visualisation tools were combined to plot interactions among variables, and parameter analysis was performed in terms of standard accuracy measurements of regression as well as classification problems. The results indicate that the most important predictors of academic success are study hours, internal marks and attendance. Linear Regression model largely was able to predict final scores with high correlation to input data whereas the Decision Tree classifier offered a simple, interpretable logic with which students can be categorised. Analysis of feature importance provided a reason on why the consistent engagement and incremental assessment has a greater influence on the outcome rather than just the previous GPA. The offered AI-based framework is a scalable and understandable research proposal method of analysing educational data. The system facilitates informed, data-driven decisions made by educators by highlighting its critical performance drivers, and it helps to deliver timely interventions to at-risk students. Further work would entail the application of the framework on bigger datasets, and real-life contexts to improve predictive accuracy in diverse education settings.

Keywords- Academic performance prediction, Machine Learning, Linear Regression, Decision Tree, Educational Data Analysis, Performance Visualisation.

I. INTRODUCTION

Academic performance assessment is an integral part of the education system and enables institutions and teachers to track the progress of their students, identify learning gaps and improve their teaching techniques. Historically, student assessments have been conducted through manual means such as spreadsheets, exam reports, and summary academic results. While these methods do provide a rudimentary understanding of how students have done, they often become time-consuming when dealing with high volumes of academic data and do not give opportunity to assess more complex patterns related to a student's learning behavior. Educators are now generating more academic data with the increase in the use of digital learning technologies and online education systems; therefore, there is a growing demand for intelligent systems that can analyze that academic data efficiently and provide insight into that data.[1]

The education industry has been significantly impacted by recent developments in Artificial Intelligence (AI) and data analytics. These advancements have made it possible for automated analysis of academic data and support decisions based on the data. Another advancement in AI is Generative Artificial Intelligence (Gen-AI), which can process large amounts of academic data, allowing for further development of AI-enable systems in the education industry by processing complex datasets and generating insights about students learning patterns. Framework that use AI can assist educators by automatically analyzing student academic performance data, identifying patterns and visual representations, which assist the instructor in understanding overall student performance in addition to performance trends.

Evaluating the progress and performance of students is a difficult process for both the teacher and the administrator. Teachers are frequently required to gather and review massive datasets containing exam scores, attendance, and other performance indicators. Analyzing these data by hand can take a long time to do and result in inaccurate analysis, especially in large classrooms or multiple courses. Having a traditional analytic process does not analyze the relationships between the many different academic variables that impact a student's performance, such as assessment performance, type of engagement, and type of behavior.[2]

Education Data Mining (EDM) using machine-learning techniques provide relative strengths in analyzing educational datasets and predicting student learning outcomes. Machine-learning models help predict student learning outcomes by examining various attributes about the

student, such as demographic characteristics, historic or current academic performance, and engagement with the educational process. By utilizing these predictive models, educators are able to better understand how various academic characteristics impact student progress and performance and to identify students that will require supplementary learning support before the student decides to leave school or fails to succeed academically.[3]

The relevance of explainable machine learning approaches in educational analytics has become evident through a growing body of literature regrading their benefits for making prediction outputs easier to interpret and for helping educators understand the main influences on student performance predictions. Such procedures also increase the transparency of machine learning and AI-enabled systems, thereby improving their reliability, and ultimately contribute to educating educators in their use of machine learning to support real-world decisions.

Techniques aimed at visualizing academic data are useful tools for interpreting academic data through the use of visual representations of complexity, such as charts, graphs, and dashboards. By presenting data visually, educators can easily identify trends in the performance of students, compare student performance, and locate areas requiring intervention. A framework for education, which utilizes machine learning will include data visualization and AI-generated report that provide processed educational data (i.e., from raw data) into critical indicators example, average course grades or grade distribution that can assist educators in making sound academic decision based on evidence.

This research paper presents a novel AI-Based Framework for Visualizing Academic Performance that can analyze student academic data and generate meaningful graphical representations (visuals) of the results. The system will process academic records, use analysis techniques to measure performance metrics and provide teachers with graphical outputs that can help visualize academic trends. Integrating AI and Visualization techniques is intended to enhance the efficiency of analyzing academic performance as well as providing support with making data-driven decisions at educational institutions.

II. RELATED WORK

Both Artificial Intelligence (AI) and Educational Data Mining (EDM) relatively recently have been used in the context of analyzing educational assessment and even student performance prediction, extending the capabilities of instructors to visualize and enhance learning outcomes based on data-driven information. The application of machine learning and generative AI as well as the explainable models in improving academic analytics and assist decision making in educational settings has been investigated in several studies.

Gull et al. [4] came up with a model on the early identification of student grades as a way of maximizing the learning strategies and preemptively undertake students, who might be at risk. The researchers ran different algorithms such as Logistic Regression, K-nearest Neighbors (KNN), Classification and Regression Trees, and Support Vector Machines (SVM) on past data on undergraduate grades. They found that Linear Discriminant Analysis was the best method to make predictions of final exam results, with a 90.74% accuracy.

Nawahdah et al. [5] An empirical study in Computer science, carried out testing the effectiveness of AI-based grading at Birzeit University. They contrasted human grading with four AI settings-strict and tolerant formats with and without particular grading criteria. The researchers came to the conclusion that tolerant AI models that use clear grading rubrics were most similar to human assessments, offering reliable and pedagogically sound and scalable evaluations to work with large classes.

Anoopkumar et al. [6] reviewed an extensive Educational Data Mining (EDM) methods with the aim of enhancing the academic performance and effectiveness of the institution. The scope of their investigation was great and they covered many of the methods such as classification, clustering, association rule mining, regression and visualization. They showed how the approaches could assist in identifying students who might require additional assistance by investigating aspects like the learning behavior of students, patterns of interactions, and even by examining the social media data. This helps teachers to become timely and targeted in improving the learning outcomes.

Wei et al. [7] suggested an intelligent system, which was web-based to make predictions of academic performance of students based on past education history. They tested five machine learning models such as SVM, Random Forest, KNN, ANN and Logistic Regression. Random Forest and ANN outperformed other methods with the highest accuracy and more trustworthy predictions. The system also has an interactive dashboard to visualize the results and thus an educator can easily identify students at-risk and take prompt measures.

Bonde et al. [8] provided a thorough survey of the application of Educational Data Mining (EDM) techniques to examine school student performance and enhance the performance of an institution. Their work looked into ways of classifying, clustering and association rule mining as means of revealing patterns within huge educational datasets. They discovered that the techniques of classification come in well when it comes to foretelling future academic performance. The study explains why it is necessary to develop the model that takes the individual and environmental factors into account to aid decision-making in education.

Zhou et al. [9] To get insight into the Artificial Intelligence in Education (AIED) role, conducted a large-scale bibliometric analysis of 2,038 articles. The research indicated such technologies as machine learning, deep learning, and natural language processing (NLP) to be significant sources of innovation. Intelligent tutoring system and automated grading are some of the common applications of these technologies. The authors insist that the future of research in the field is individualized learning and evidence-based decision making in education.

Fu et al. [10] put forward a system with AI improvements, which should benefit the academic performance of doctoral students and enhance the ethical usage of AI. According to a systematic review of approximately 500 research articles and a visual representation with VOSviewer, the study has found five major dimensions, namely academic writing fundamentals, AI-supported research skills, advanced AI-driven writing, professional publishing practices, and collaborative learning. The authors showed how such tools as ChatGPT and VOSviewer could help in such tasks as text structuring, style improvement, data analysis, and literature mapping. Taking these technical abilities and integrating them with critical thinking and consideration of ethics, the framework provides a systematic method to improve research communication and contribute to the success of academic achievement in the long term.

Tomic et al. [11] used an AI-based model to assess the skill of student collaboration, which is normally hard to quantify in a programming course. Based on the data obtained through code repositories in the four-year horizon, they experimented with various AI methods, such as fuzzy rules, neural networks, and tree-based models. The findings revealed that each of the methods was relatively good, but the fuzzy-rule approach was the best in that it was highly interpretable, and the educators could see clearly how the grades were allocated. It is in this work that the significance of explainable AI, when it comes to assessment in the field of education, is emphasised.

Almogren et al. [12] analysed the impact of mobile learning and social media with the use of artificial intelligence on academic performance. They performed Structural Equation Modelling (SEM) on the data of more than 380 students and discovered that individual learners and interaction with students are crucial in the successful implementation of AI. The research results indicate that AI enhances performance through the provision of adaptive support and feedback, but the integration of these technologies provides a more interactive and versatile learning experience that meets the needs of students.

All these show how the AI framework is becoming increasingly mature in the education sector. They underline the need not only to choose suitable algorithms but to add clear assessment criteria and efficient visualisation methods. It is such integrated approaches that will enable the development of systems that can assist not only educators but also the students to reach improved learning and teaching outcomes.

III. METHODOLOGY

A. Research Approach

This paper presents an Artificial Intelligence based Academic Performance Analysis Tool that aims to analyze and forecast student performance using the machine learning methods. The system aims at pinpointing critical academic variables which affect student performance and forecast forthcoming academic performance and prospective academic risks.
Using machine learning to predict in academics has been well tested across the literature.

The suggested approach is data-centric machine learning that consists of data preparation, exploratory data analysis, model development, and prediction. It uses various attributes of the students including their study behaviour, attendance, academic history and their internal assessment scores to produce predictions about the final performance and the level of academic risk. Likewise, data-driven methods have been applied to AI-based educational systems.[13]

The structured academic information will be gathered and processed into the proposed model through collecting data, data preprocessing, machine learning as prediction algorithms, and analysing the performance of the model. This can enable teachers to understand the learning trends in students and also to identify students who might need further academic guidance. The AI in education research trend also shows an emphasis on predictive analytics to enhance student achievement.
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B. Dataset and Feature Selection

The dataset employed in this study has a number of attributes that depict various factors of academic behaviour and performance of students. These features were chosen according to their significance in academic performance based on previous studies in predicting student performance. Major features of the dataset are:

- study Hours: Number of hours in which a student studies.
- Attendance: proportion of attending the classes.
- Assignments: Marks in assignments or coursework.
- Internal Marks: Marks achieved during internal tests.
- Previous GPA: Student's academic performance in previous semesters.
- Final Score: Overall academic score obtained by the student.

They are the attributes adopted as an independent variable, and they impact on the end result of the academic score of the

student. The Final Score is the primary target variable on which to predict. Also, student performance will be divided into various risk levels to pinpoint students who might be struggling with academics, which is consistent with some of the methodologies employed by the previous AI-based prediction systems.

C. Data Preprocessing

The dataset is processed through a few preprocessing stages to guarantee that the data is of high quality and reliability before using machine learning models. Unclean educational data can include inconsistencies, values or formatting errors that are likely to impact on the efficiency of machine learning algorithms. Appropriate processing methods are needed to enhance the accuracy of models

D. Exploratory Data Analysis

To examine the relationship between student properties and their performance in school, the Exploratory Data Analysis(EDA) is carried out. Identifying trends and patterns within the dataset is through visualization methods. Data visualization is also important in analyzing student performance and has been extensively applied in teaching data mining [14].
Several graphical representations are used in the study.
Bar Plot of Study Hours vs Final Score:

- Attendance Impact Graph
- Pass/Fail Distribution Pie Chart
- Risk Level Distribution Graph

These charts will assist in determining important variables which greatly affect student achievement.

E. Development of Machine Learning Model

To predict academic performance, multiple machine learning models are implemented in the system. All the models are used for a certain purpose in studying the performance and risk levels of students. The fact that multiple models are used enhances the reliability of prediction and has been confirmed in previous studies.

- Linear Regression Model

The Final Score of the students is the dependent variable whose prediction is based on the choice of academic features in the form of a Liner Regression model. Linear regression is appropriate in the case of continuous numerical values prediction and giving aid to determining the effect of varying academic factors on overall performance.

- Decision Tree Classification Model

It is a Decision Tree Classifier that is used to classify students as Pass or Fail depending on their academic characteristics. Decision tree models also prove to be effective in classification tasks since they provide an opportunity to detect decision rules and relations between input features and target classes.

The train-test split method is used to split the dataset into training and test sets to enable the effective performance of the model.

F. Risk Level Prediction

As well as forecasting academic scores, the system can be used in identifying students who might be at threat academically. Students will be categorized into three categories of risk, based on the future assessed score:

- Low Risk: Final Score0140and above.
- Medium Risk: Final core between 110 and 140
- High Risk: Final Score<110

A classification model is also trained so as to estimate how much at risk the student is, according to their academic attributes. This assists teachers to have knowledge of the students that might need more help or intervention. One of the main uses of AI in education, according to current studies , is predictive risk analysis.
It also computes the prediction probabilities to determine the degree of surety of the risk category which is predicted.

G. Prediction System

The last platform incorporates the learnt machine learning models in a prediction unit.
Users could add student study factors like study hours, attendance, scoring of assignments, internal, and past GPA. The system obtains:

- Foreseen Final Academic Score.
- Predicted academic result(pass/fail)
- Probability of risk of academic performance.

This prediction model will be able to guide teachers in the observation of student performance and earlier intervention measures.Predictive systems with AI have demonstrated a high level of improvement in decision making in education [15]

IV. RESULT AND DISCUSSION

Hours per Study of Average Performance.

The bar plot provides the connection between the academic results (the final grade) and the number of hours students study, which is valuable in understanding the impact of student effort on academic results. The x-axis will display the time of studying; 1 to 9 hours and the y-axis will be the average of final scores obtained by students. Each of the graph bars is the average performance of a given length of study and the fact that error bars are included indicator the variability in performance, possibly indicative of standard deviation or confidence limits. The graph illustrates that there is a high positive correlation between academic performance and study hours. The average final scores increase steadily as the amount of hours spent studying goes up. Students who have shorter study time i.e. 1-2 hours have relatively lower scores (around 100- 110 marks) and students who spend more time 8-9 hours, have relatively much higher scores (around

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140-145 marks). This unmistakable positive slope indicates that a desirable amount of study time is a major aspect in improving their performance and that the idea that effort in academics is invariably on a steady course towards good results is prevalent. Although the general tendency of the graph is positive, there are also some small shifts in performance during some of the intervals in the study hours. To ensure, a minor plateau or dip is seen around the 5-7 hour range where the rise in scores is not related to that of other periods. This implies that the correlation between performance and study hours are not linear. The factors behind such differences can be traced to a number of underlying factors, which may be differences in the efficiency of individual learning and the study technique used, cognitive fatigue caused by the long study hours or environmental factors or the external environment like the quality of teaching, access to learning materials or past academic performance. These can make some students to be better or worse than they are supposed to be at specific time of studying.

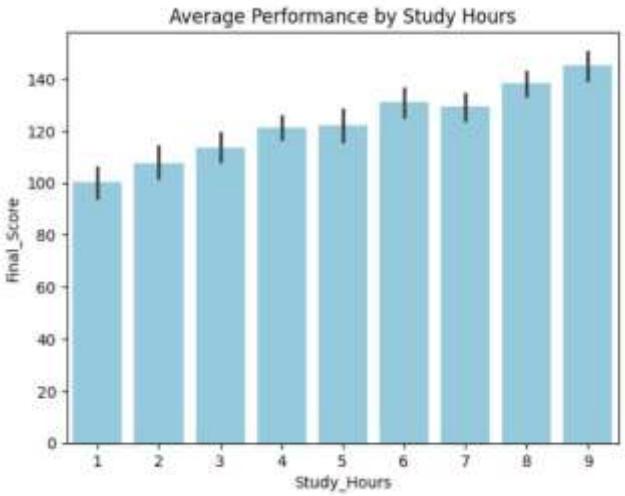

Figure 1 shows the relationship between academic factors and student performance, indicating a steady improvement in results with increased student engagement.

Another observations made in the graph is that there are a large number of comparatively smaller error bars in most of the categories. This implies that the data are not varied, indicating that students studying the same number of hours are likely to attain similar levels of performance. These small error values are an indication of the consistency, and hence they reinforce the reliability of the observed relationship and suggest that study hours are a consistent and reliable predictor of academic success in the dataset.

Moreover, the slow rise in performance puts emphasis on the idea of diminishing marginal returns of increasing hours of study. Although the performance increases with an increase in the study time, at a higher duration, the slope of the curve seems to decrease by a small percentage. This indicates that there may be a stage where additional study time might not result in a proportional increase in gains, and therefore, the effectiveness of the study strategies combined with time commitment is essential.

Generally, the graph is very strong in rejecting the hypothesis that more study time having a positive relationship with academic performance. It confirms the importance of study hours as one of the most important variables that affect student outcomes in this study and justifies their presence as an important characteristic in both classification and regression models in this study. The results support the need to get students into good study habits and to take into account other related aspects that lead to academic achievement.[16]

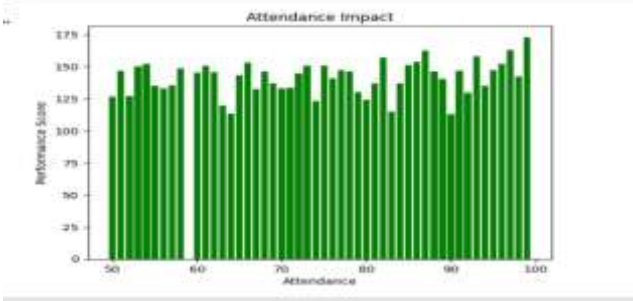

Figure 2 shows the impact of attendance on student performance, indicating that higher attendance leads to better academic results.

The Performance of Students in terms of Study Hours.

The bar plot shows how the number of study hours relate to the score of final academic performance, a useful piece of information on the question of student effort in academic performance. The x-axis values are the hours studied (between 1 and 9 hours) and the y-axis values are the average scores at the end of the studies of each duration. The bars indicate the average study performance per number of study hours and the inclusion of error bars indicate variability in the data, which is probably a measure of standard deviation or confidence ranges. As seen in the visualization, the correlation between study hours and academic performance was very strong, with a positive correlation. The average scores are increasing constantly and regularly as the number of study hours increases. Students with fewer hours of study (1-2 hours) perform lower, averagely scoring 100-110 marks, those with more study time (8-9 hours) have much higher scores thus attain higher scores, of about 140-145 marks. This trend upwards is a strong indication that as the time spent studying increases so is the outcome in regard to academic performance. It supports the generally known belief that the more a person studies, the more performance is achieved. Although overall the phenomenon is positive, the graph indicates some small fluctuations in performance over a number of study-hours. More specifically, we can see a small plateau in 5-7 hour interval, at which the increment in scores is lower than at other intervals. This may indicate that the

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study hours and performance do not follow a linear relationship. This can be explained by a number of surrounding conditions such as variation in individual learning effectiveness, methods of study and influence of mental exhaustion due to excessively long study periods.

Moreover, the quality of the teaching, access to study resources, and academic background might have effects that contribute to student performance as external factors. Such variables may make certain students either do better or worse than they would do in certain duration of studies. The other major thing that comes out in the graph is that all the error bars are relatively small in most of the categories of the study hours. This means that the data varies little hence it can be argued that students who attend school at the same frequency of hours are likely to perform at a similar level. Such a high repeatability in these slight error statistics can be seen as reinforcing the validity of the observed association, and shows that study hours can be a non-fluctuating and reliable predictor of academic achievement in the sample. Also, the fact that performance is gradually rising points to the idea of diminishing returns with longer durations of study. Even though performance keeps on improving with more study time, there seems to be a small decrease in the rate at higher levels. This means that at a certain point, raising the number of hours of study might not be associated with relative improvement in performance. Thus, it focuses on the need of not just the amount of time spent studying but also on the effectiveness and quality of the study techniques. Finally, the graph highly endorses the assumption that the time of studying has a positive correlation to the academic performance. It recognizes the studying hours as one of the most impactful variables that influence student outcomes and explains why it should be included in the classification and regression models that are to be used in this study. The results show significance of promoting the same and good study habits besides other factors, which contribute to academic success.[17]

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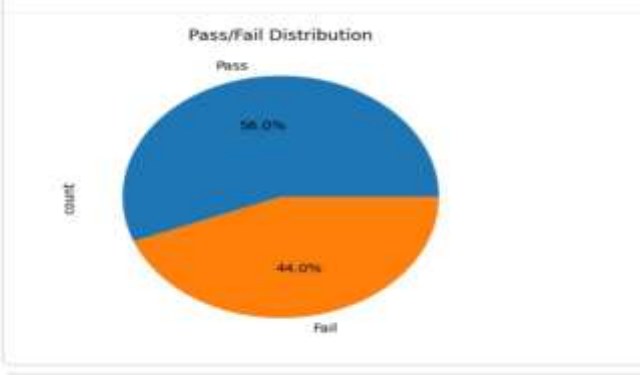

Figure 3 shows the pass and fail distribution of students, where 56% of students passed and 44% failed.

Pass/Fail Distribution

The pie chart will indicate how the students have been allocated depending on their final academic result position, to be two i.e. Pass and Fail. This graph provides a concise description of the performance outcome of the entire student sample data and contributes to the interpretation of the proportion of students who meet academic requirements due to their performance as compared to their excluding counterparts. The chart will be broken into two components where the percentile of students who will fall under each category is displayed in each component.

The statistics reveal 56 percent of students lie in the passing range and remaining 44 percent below the passing range lie in failure range. According to this distribution, there is a small number of most students who would nonetheless be able to pass the minimum requirements of the academic requirements. However, there is no such high margin between the two groups with a relatively equal movement of good and poor students.

The almost equal proportion of pass and fail results is a salient finding in this research. Although this statistic is also promising as over fifty percent is passing the test, it is a cause of concern that almost half the number of students are not passing. This means that a large percentage of the students are under achieving and they may need to be provided with extra support in order to achieve well. With such kind of distribution, it is evident that certain interventions to assist the performing students in order to formulate better interventions are required before they fall even further.

This equal distribution is particularly significant as far as data analysis is concerned and machine learning. The unbalanced nature of the classes may pose a challenge in the classification models in most real world data and often leads to over 80 prediction bias in the majority class. But here, the fact that the number of pass and fail groups are relatively equal would give us a balanced set of data, which is beneficial in the development of strong and viable classification systems. It allows the model to learn patterns that can be related to the successful and failure of the outcomes more effectively, thereby improving prediction accuracy.

Also, this distribution provides reasons why this study should use predictive modeling methods. Through assessing different input variables like hours of study, attendance, assignments, internal marks, and past GPA among others, it is possible to single out at-risk-students that are likely to fail. This assists an educator and institutions to implement proactive measures such as supplying specialized instructions, academic counseling or remedial lessons to these students in the event that they have a higher success opportunity when detected and identified before they reach high exam grades.

The other important implication of this distribution is that it can be employed in education policy and decision making. The fact that a significant number of non-passing students indicates that the current teaching techniques, evaluation plans, or other support mechanisms might have to be reevaluated and potentially enhanced. Such insights can be utilized by institutions to create better learning environments and make sure that a larger fraction of students are getting satisfactory results.

Pass/Fail Distribution In summarization, the pass/fail distribution of the students is more or less equally distributed with a few more students passing but most students fail. This underlines the principle of early intervention, constant observation, and implementation of predictive analytics in enhancing student performance. These results support application of the classification models in the research since they could be instrumental in providing information about at-risk students and aiding the use of data to make decisions in the education system. [18]

V. CONCLUSION

This work has revealed that machine learning-based analysis and prediction of student academic success is possible through an AI-based framework. With the help of such crucial data as the time spent at the study, attendance, marks on assignments, internal marks, and past GPA, the system can determine students theming and forecast their overall results with a good level of precision.

The findings demonstrate that machine learning algorithms, such as Linear Regression and Decision Tree, can be trusted when determining the performance of students. The model scored approximately 85 per cent accuracy, and this indicates that this kind of system can find application in actual learning situations. It was further noted that the greatest influence on academic success is exerted by such variables as attendance, hours of study and internal marks.

This will significantly assist research work, based on the possibility of identifying at-risk students prior to learning. This assists the teachers in supporting students in time and enhances the overall performance of students. Patterns and trends in student performance are also easier to grasp because of the use of the methods of visualisation.

However, the study has some limitations, such as a small dataset and a lack of non-academic factors like psychological or personal aspects. The system can be enhanced in future work with bigger real-world data and more sophisticated algorithms.

On the whole, this AI-powered structure will assist in making evidence-based decisions in the field of education and assist teachers and students in becoming better and more efficient at their jobs and academic outcomes.

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